Addressing and Presenting Quality of Satellite Data via Web-based Services

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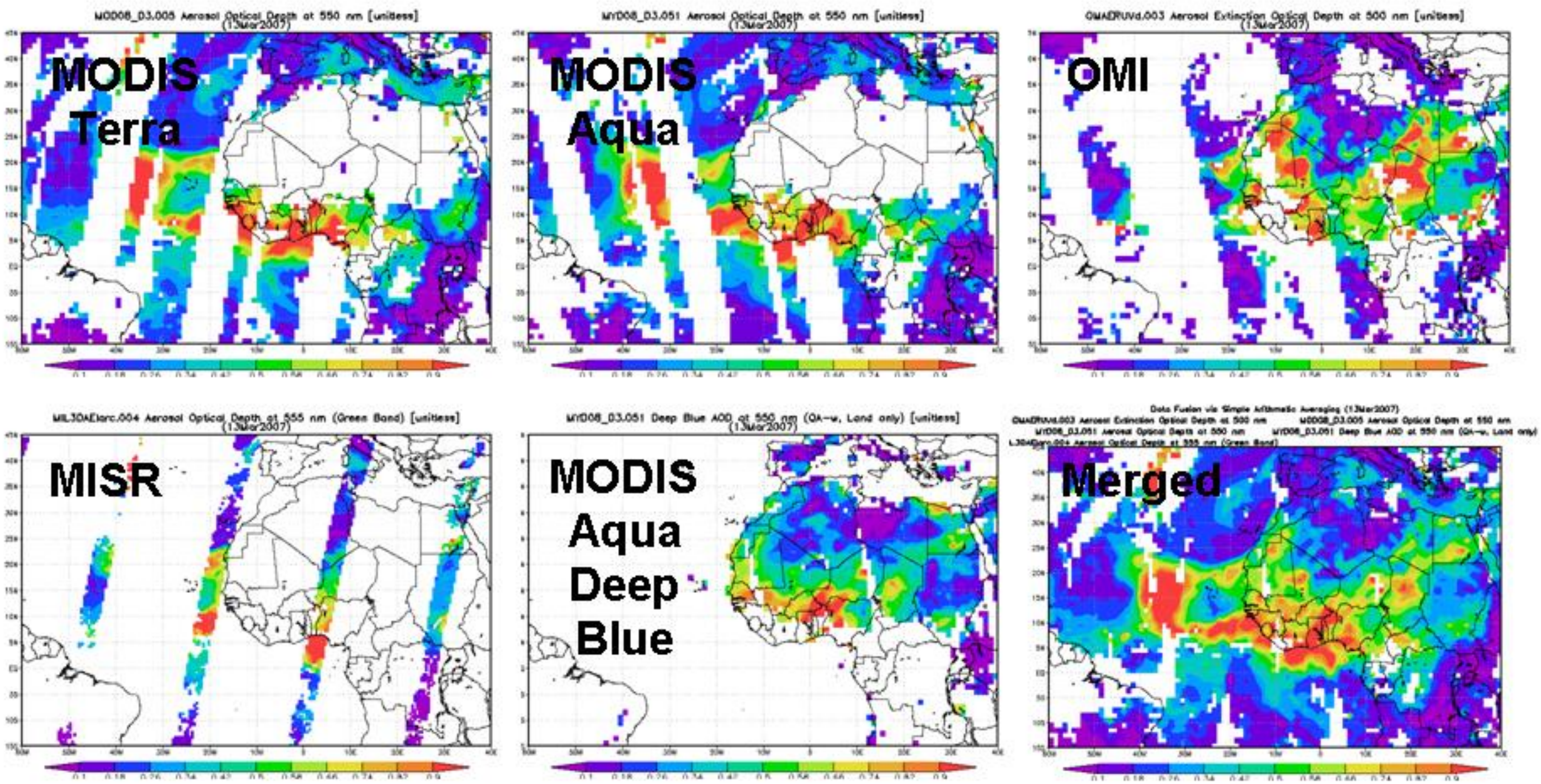
Data merging example: aerosols from multiple sensors

March 13, 2007



Merged AOD data from 5 retrieval algorithms (4 sensors: MODIS-Terra, MODIS-Aqua, MISR, and OMI) provide almost complete coverage.

Caveat: this is just the simplest merging prototype in Giovanni

Challenges in dealing with Data Quality

Why so difficult?

•Quality is **perceived differently** by data providers and data recipients.

•**Many different qualitative and quantitative aspects** of quality.

•No comprehensive **framework** for **remote sensing data quality**

•**No preferred methodologies** for solving many data quality issues

•Data quality aspect had lower priority than building an instrument, launching a rocket, collecting/processing data, and publishing a paper using these data.

•Each science team handled quality differently.

What has changed?

With the recent revolutionary progress in data systems, the data from many different sensors easily arrive to users.

Only now, a systematic approach to remote sensing quality is on the table.

•NASA is beefing up efforts on data quality: ROSES 2010

•ESA funded GeoViQua (Feb 2011 – Jan 2014) for integrating quality and visualisation of quality in GEOSS

•QA4EO: an international effort to bring communities together on data quality

•ESIP Federation created a new Information Quality Cluster. Summer 2011 ESIP meeting's main theme is Information and Data Quality.

•AGU and EGU sessions on data quality.

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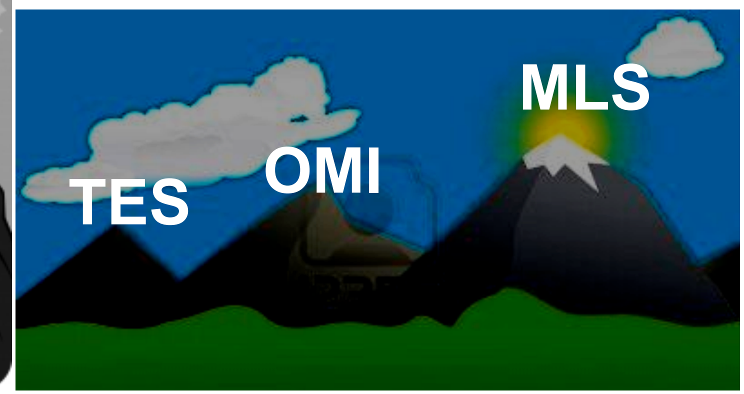
Challenges addressed

- Identifying Data Quality (DQ) facets
- Finding DQ
- Capturing DQ
- Presenting DQ
- Presenting DQ via web services

Different perspectives

We have good data

We have good data

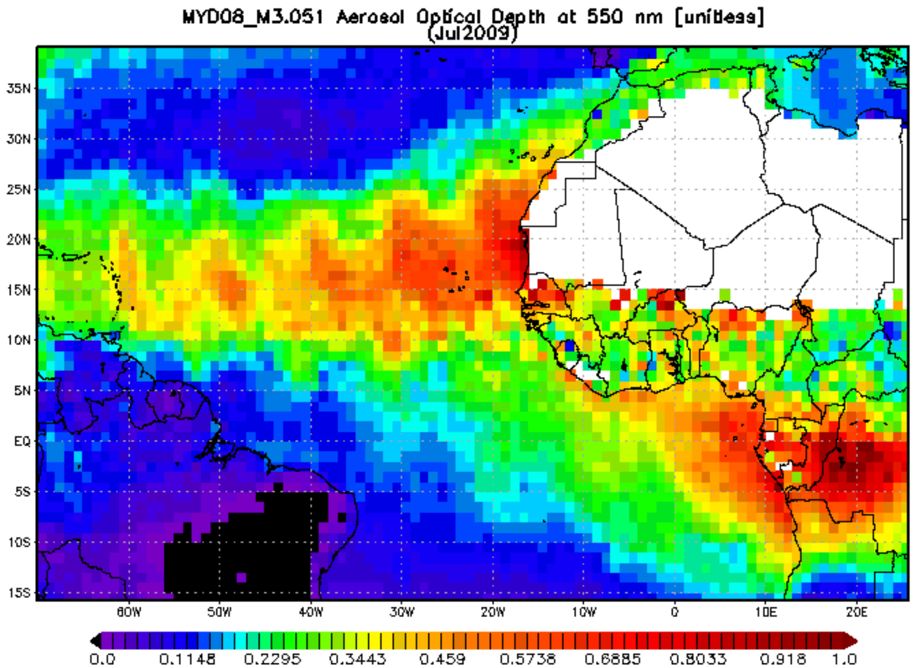


Data quality needs: fitness for purpose

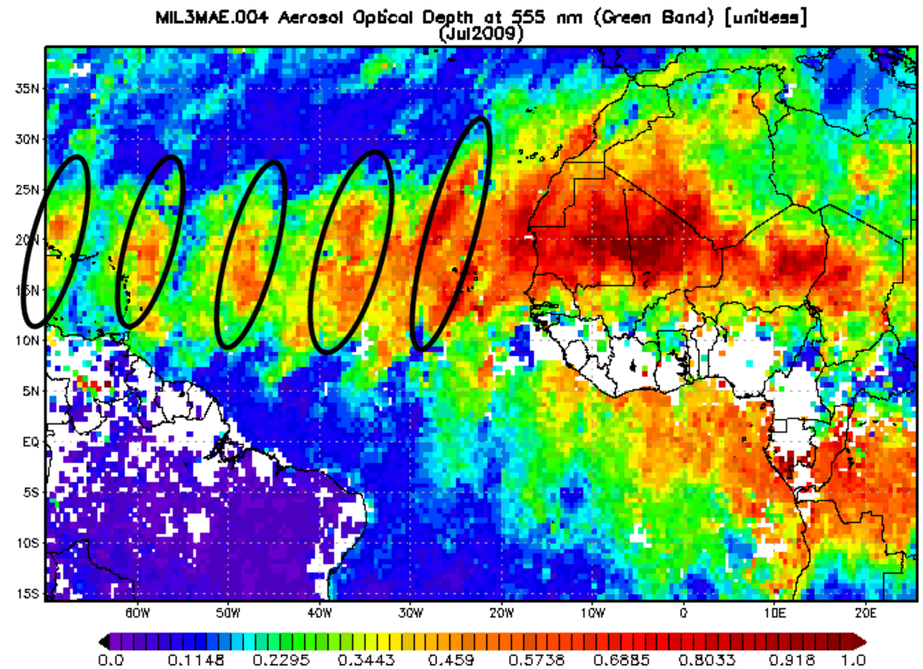
- Measuring Climate Change:
  - *Model validation*: **gridded contiguous data with uncertainties**
  - *Long-term time series*: **bias assessment** is the must , especially sensor degradation, orbit and spatial sampling change
- **Studying phenomena using multi-sensor data:**
  - **Cross-sensor bias** is needed
- **Realizing Societal Benefits through Applications:**
  - *Near-Real Time for transport/event monitoring* - in some cases, **coverage and timeliness** might be more important that accuracy
  - *Pollution monitoring* (e.g., air quality exceedance levels) – **accuracy**
- **Educational** (users generally not well-versed in the intricacies of quality; just taking all the data as usable can impair educational lessons) – **only the best products**

Example: How to quantify sampling aspect of aerosol L3 data to make it useful?

MODIS Aqua AOD July 2009



MISR Terra AOD July 2009



- *Completeness*: MODIS dark target algorithm does not work for deserts
- *Representativeness*: monthly aggregation is not enough for MISR and even MODIS
- *Spatial sampling* patterns are different for MODIS Aqua and MISR Terra: "pulsating" areas over ocean are oriented differently due to different orbital direction during day-time measurement → *Cognitive bias*

What is Level 3 data quality?

It is not well defined in Earth Science....

- If Level 2 errors were known, the corresponding Level 3 error could have been computed, *in principle*
- Processing from L2→L3 daily → L3 monthly may reduce random noise but can also exacerbate systematic bias and introduce additional sampling bias
- At best, standard deviations and sometimes pixel counts are provided
- However, these standard deviations come from convolution of natural variability with sensor/ retrieval uncertainty and bias – need to be disentangled
- Biases are not addressed in the data themselves

Why can't we just apply L2 quality to L3?

*Aggregation to L3 introduces new issues where aerosols co-vary with some observing or environmental conditions – **sampling bias:***

- *Spatial*: sampling polar areas more than equatorial
- *Temporal*: sampling one time of a day only *(not obvious when looking at L3 maps)*
- *Vertical*: not sensitive to a certain part of the atmosphere thus emphasizing other parts
- *Contextual:* bright surface or clear sky bias
- *Pixel Quality*: filtering or weighting by quality may mask out areas with specific features

Factors contributing to uncertainty and bias in L2

- *Physical*: instrument, retrieval algorithm, aerosol spatial and temporal variability…
- *Input*: ancillary data used by the retrieval algorithm
- *Classification*: erroneous flagging of the data
- *Simulation*: the geophysical model used for the retrieval
- *Sampling*: the averaging within the retrieval footprint

Error propagation in L2 data

- Instruments are usually well calibrated according to the well established standards.
- In the majority of cases, the instrument uncertainty very rarely is propagated through L2 processing.
- As a result, L2 uncertainty is assessed only after the fact.
- Validation is performed only in few locations, and then the results are extrapolated globally.

In the absence of computed uncertainty, various methods have been recently applied to emulate L2 data uncertainty

- Perturbing the retrieval algorithm parameters
- Bootstrap simulation
- .....

Quality Control vs. Quality Assessment

- Quality Control (QC) flags in the data (assigned by the algorithm) reflect “happiness” of the retrieval algorithm, e.g., all the necessary channels indeed had data, not too many clouds, the algorithm has converged to a solution, etc.

- Quality assessment is done by analyzing the data “after the fact” through validation, intercomparison with other measurements, self-consistency, etc. It is presented as bias and uncertainty. It is rather inconsistent and can be found in papers, validation reports all over the place.

Different kinds of reported data quality

- Pixel-level Quality: algorithmic guess at usability of data point
  - Granule-level Quality: statistical roll-up of Pixel-level Quality
- Product-level Quality: how closely the data represent the actual geophysical state
- Record-level Quality: how consistent and reliable the data record is across generations of measurements

Different quality types are often erroneously assumed having the same meaning

Ensuring Data Quality at these different levels requires different focus and action

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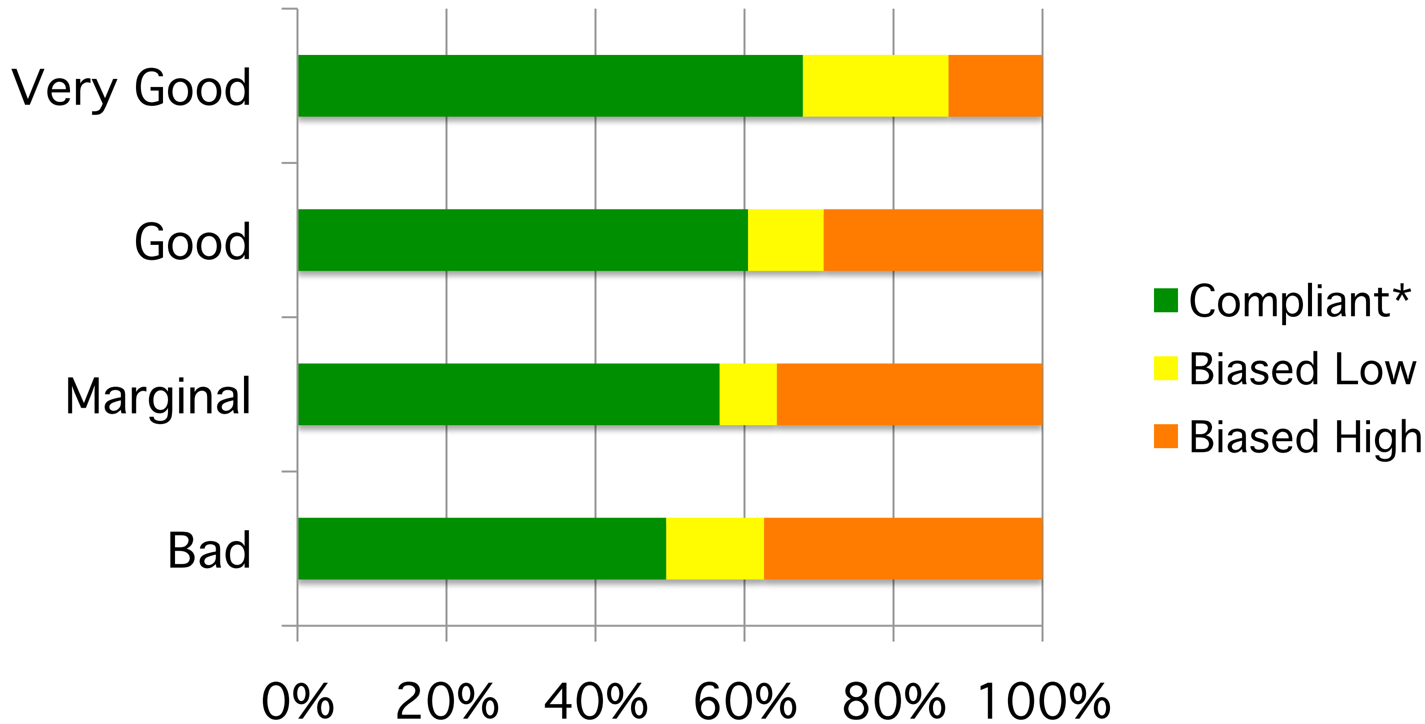
Percent of Biased Data in MODIS Aerosols Over Land Increase as Confidence Flag Decreases



*Compliant data are within $\pm$ 0.05 $\pm$ 0.2 $_{\text{Aeronet}}$

Statistics from Hyer, E., J. Reid, and J. Zhang, 2010, An over-land aerosol optical depth data set for data assimilation by filtering, correction, and aggregation of MODIS Collection 5 optical depth retrievals, Atmos. Meas. Tech. Discuss., 3, 4091–4167.

General Level 2 Pixel-Level Issues

- How to extrapolate validation knowledge about selected Level 2 pixels to the Level 2 (swath) product?
- How to harmonize terms and methods for pixel-level quality?

AIRS Quality Indicators

0 Best
1 Good
2 Do Not Use

Data Assimilation
Climatic Studies

Match up the recommendations?

Purpose

MODIS Aerosols Confidence Flags

Ocean	Land
3 Very Good	3 Very Good
2 Good	2 Good
1 Marginal	1 Marginal
0 Bad	0 Bad

Use these flags in order to stay within expected error bounds

Ocean	Land
±0.03 ± 0.10 t	±0.05 ± 0.15 t

Data Quality vs. Quality of Service

- A data product could very good,
- But if not being conveniently served and described, is perceived as not being so good...

User perspective:

- There might be a better product somewhere but if I cannot easily find it and understand it, I am going to use whatever I have and know already.

Examples of Quality Indicators

- Terminology: Quality, Uncertainty, Bias, Error budget, etc.
- Quality Indicators:
  - **Completeness:**
    - *Spatial* (MODIS covers more than MISR)
    - *Temporal* (Terra mission has been longer in space than Aqua)
    - *Observing Condition* (MODIS cannot measure over sun glint while MISR can)
  - **Consistency:**
    - *Spatial* (e.g., not changing over sea-land boundary)
    - *Temporal* (e.g., trends, discontinuities and anomalies)
    - *Observing Condition* (e.g., exhibit variations in retrieved measurements due to the viewing conditions, such as viewing geometry or cloud fraction)
  - **Representativeness:**
    - Neither pixel count nor standard deviation fully express how representative the grid cell value is
    - ……

Finding data quality information?

What do we want to get from the documentation?

The known quality facts about a product presented in a structured way, so computers can extract this information.

Algorithm Theoretical Basis Document (ATBD):

- More or less structured
- Usually out-of-date
- Represents the algorithm developer perspective
- Describes quality control flags
- Does not address the product quality aspects

Scientific papers as source

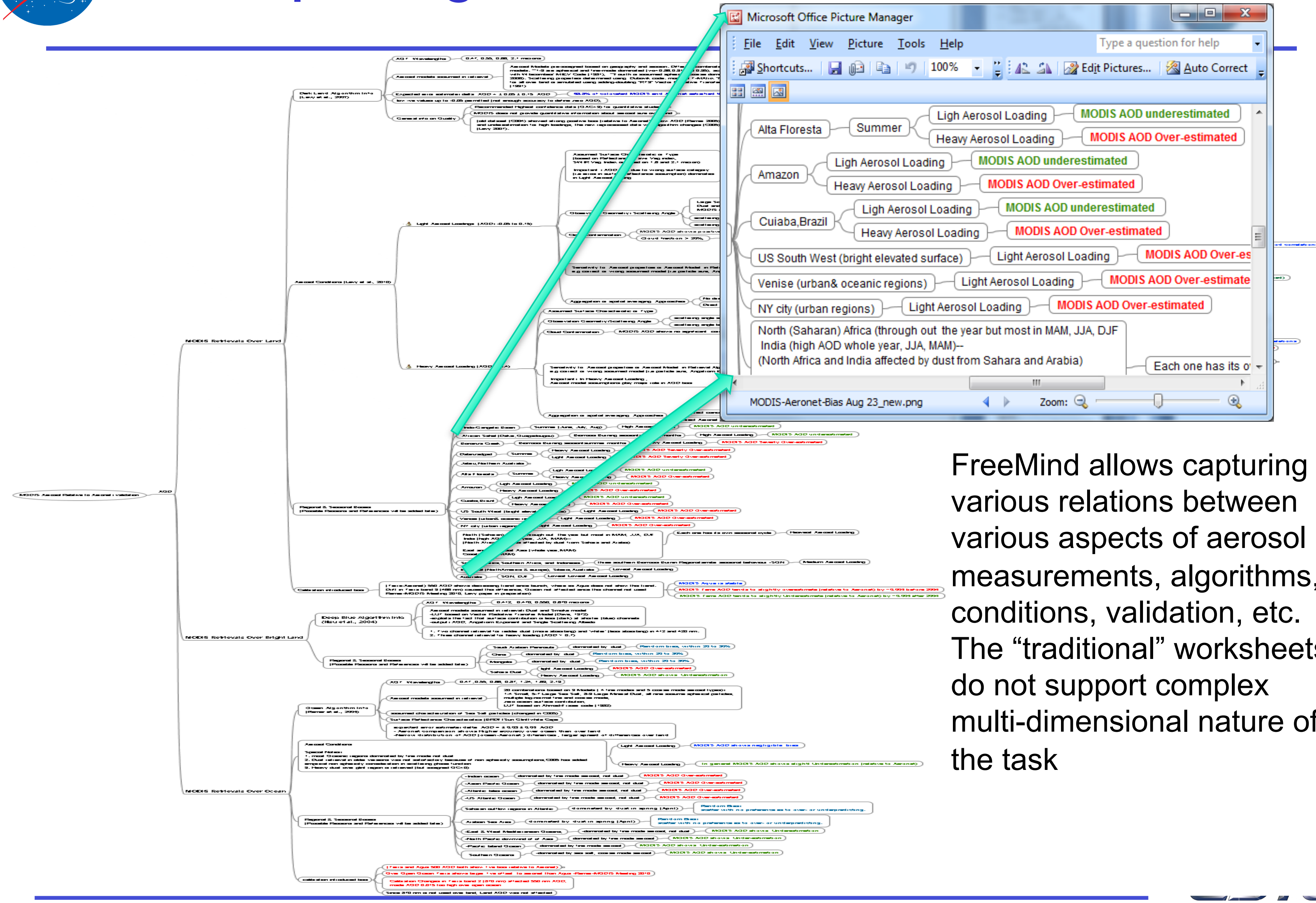
Regular papers:

- To be published, a paper has to have something new, e.g., new methodology, new angle, new result. Therefore, by design, all papers are different
- Results presented differently
- Structured for publication in a specific journal.
- Depending on a journal, the focus is different or on climate
- Version of the data not always obvious
- Findings about the old version data usually are not applicable to the newest version

Validation papers:

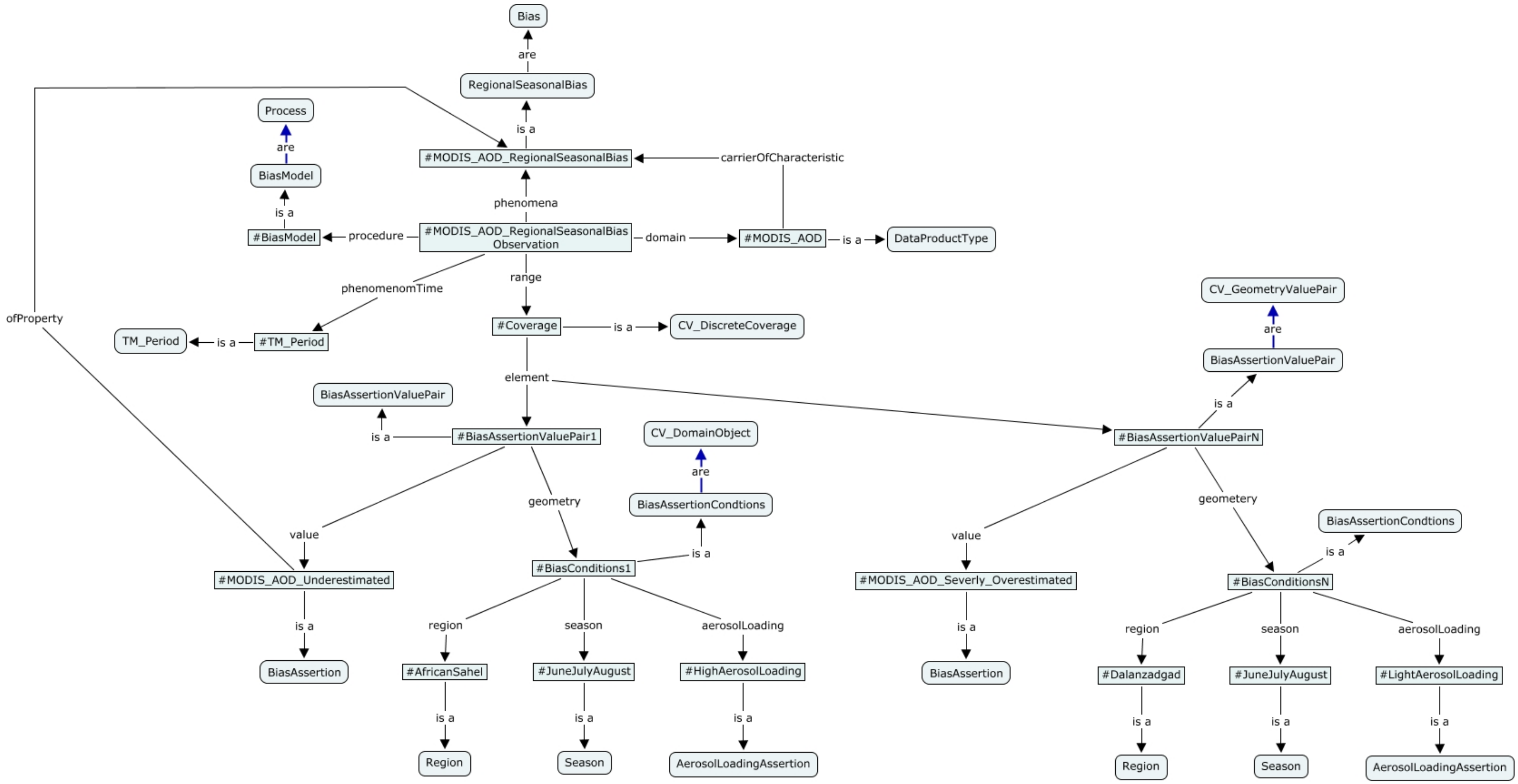
- Organized as scientific papers
- Target various aspects of validation in different papers

Capturing Bias information in FreeMind



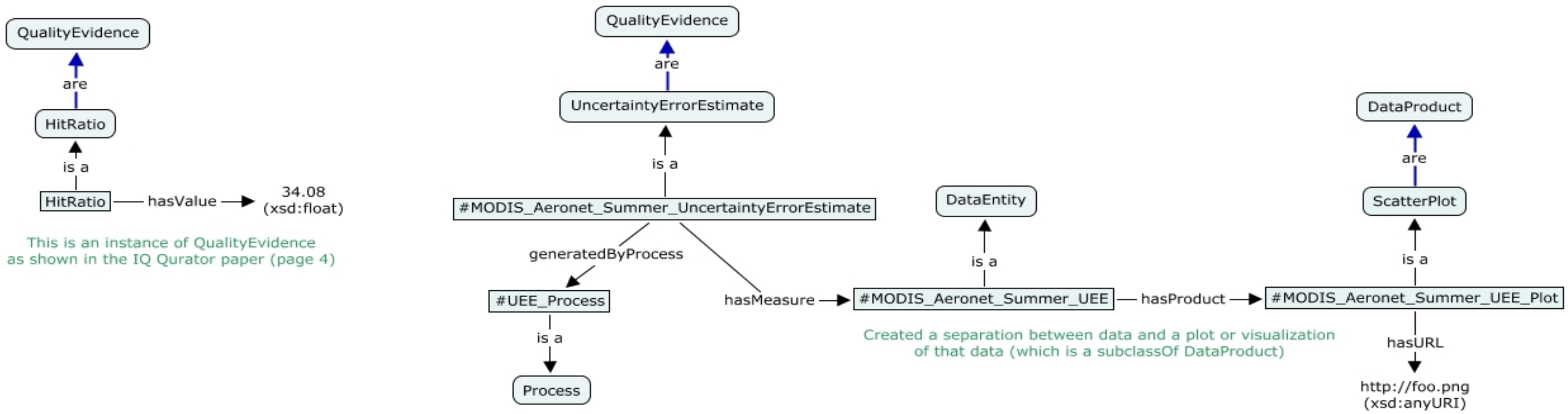
FreeMind allows capturing various relations between various aspects of aerosol measurements, algorithms, conditions, validation, etc. The “traditional” worksheets do not support complex multi-dimensional nature of the task

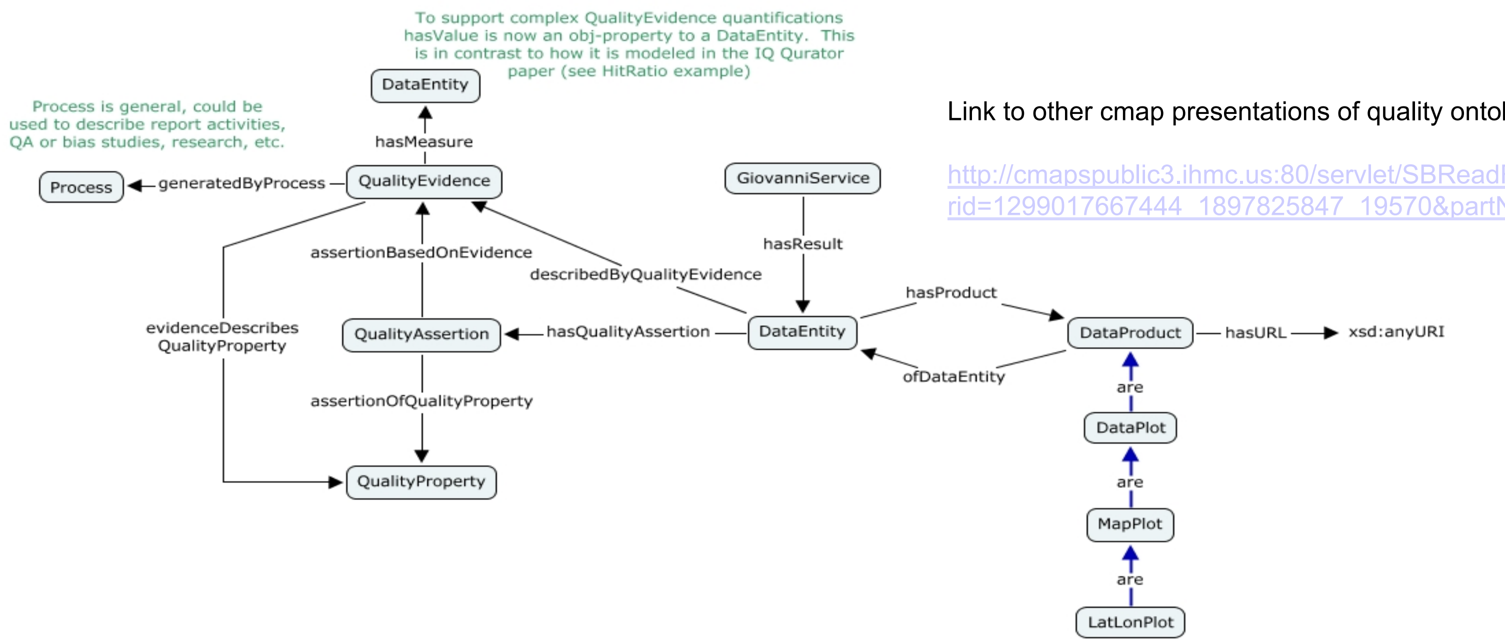
Data Quality Ontology Development (Bias)



http://cmapspublic3.ihmc.us:80/servlet/SBReadResourceServlet?rid=1286316097170_183793435_22228&partName=htmltext

Modeling quality (Uncertainty)





Link to other cmap presentations of quality ontology:

http://cmapspublic3.ihmc.us:80/servlet/SBReadResourceServlet?rid=1299017667444_1897825847_19570&partName=htmltext

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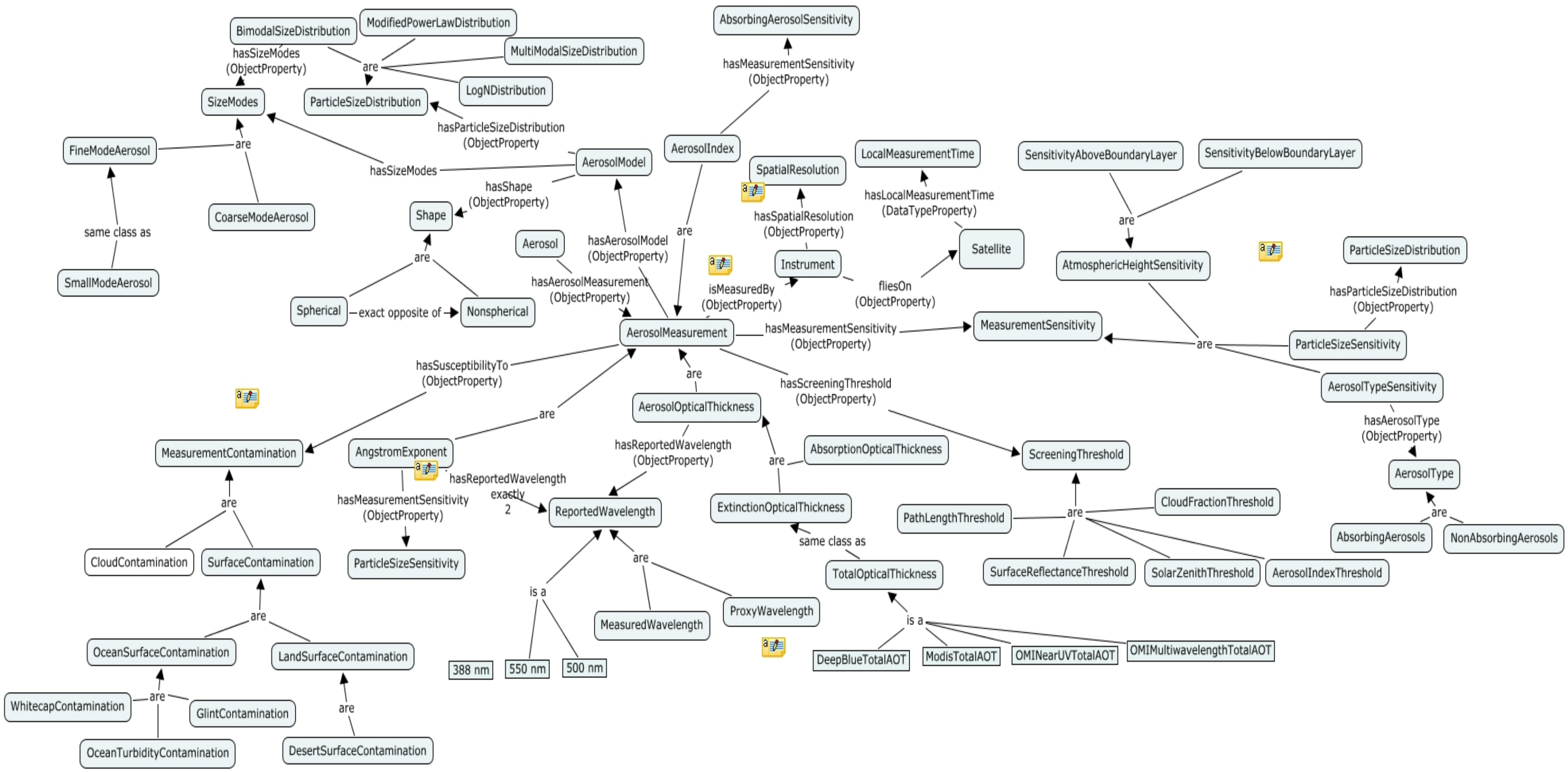
MDSA Aerosol Data Ontology Example



Ontology of Aerosol Data made with *cmap* ontology editor

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Presenting data quality to users

Data Quality Use Case: MODIS-Terra AOD vs. MISR-Terra AOD

Short Definition

- Describe to the user caveats about multiple aspects of product quality differences between equivalent parameters in two different data products: MODIS-Terra and MISR-Terra.

Purpose

- The general purpose of this use case is to inform users of completeness and consistency aspects of data quality to be taken into consideration when comparing or fusing them.

Assumptions

- Specific information about product quality aspects is available in validation reports or peer-reviewed literature or can be easily computed.

Quality Comparison Table for Level-3 AOD (Global example)

Quality Aspect	MODIS		MISR	
Completeness				
Total Time Range	Platform	Time Range	2/2/200-present	
	Terra	2/2/2000-present		
	Aqua	7/2/2002-present		
Local Revisit Time	Platform	Time Range	Platform	Time Range
	Terra	10:30 AM	Terra	10:30 AM
	Aqua	1:30 PM		
Revisit Time	global coverage of entire earth in 1 day; coverage overlap near pole		global coverage of entire earth in 9 days & coverage in 2 days in polar region	
Swath Width	2330 km		380 km	
Spectral AOD	AOD over ocean for 7 wavelengths (466, 553, 660, 860, 1240, 1640, 2120 nm); AOD over land for 4 wavelengths (466, 553, 660, 2120 nm (land)		AOD over land and ocean for 4 wavelengths (446, 558, 672, and 866 nm)	
AOD Uncertainty or Expected Error (EE)	+-0.03+- 5% (over ocean; QAC > = 1) +-0.05+-20% (over land, QAC=3);		63% fall within 0.05 or 20% of Aeronet AOD; 40% are within 0.03 or 10%	
Successful Retrievals	15% of Time		15% of Time (slightly more because of retrieval over Glint region also)	

Completeness: Observing Conditions for MODIS AOD at 550 nm Over Ocean

Region	Ecosystem	% of Retrieval Within Expected Error	Average Aeronet AOD	AOD Estimation Relative to Aeronet
US Atlantic Ocean	Dominated by Fine mode aerosols (smoke & sulfate)	72%	0.15	Over- estimated (by 7%) *
Indian Ocean	Dominated by Fine mode aerosols (smoke & sulfate)	64 %	0.16	Over- estimated (by 7%) *
Asian Pacific Oceans	Dominated by fine aerosol, not dust	56%	0.21	Over-estimated (by 13%)
“Saharan” Ocean	Outflow Regions in Atlantic dominated by Dust in Spring	56%	0.31	Random Bias (1%) *
Mediterranean	Dominated by fine aerosol	57%	0.23	Under- estimated (by 6%) *

***Remer** L. A. et al., 2005: **The MODIS Aerosol Algorithm, Products and Validation.** Journal of the Atmospheric Sciences, Special Section. **62**, *947-973.*

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Title: *MODIS Terra C5 AOD* vs. *Aeronet* during *Aug-Oct Biomass burning in Central Brazil*,

***(General)* Statement**: ***Collection 5 MODIS AOD at 550 nm* during *Aug-Oct* over Central South America *highly* over-estimates for *large AOD* and in non-burning season *underestimates* for *small AOD*, as compared to Aeronet; *good* comparisons are found at *moderate AOD*.**

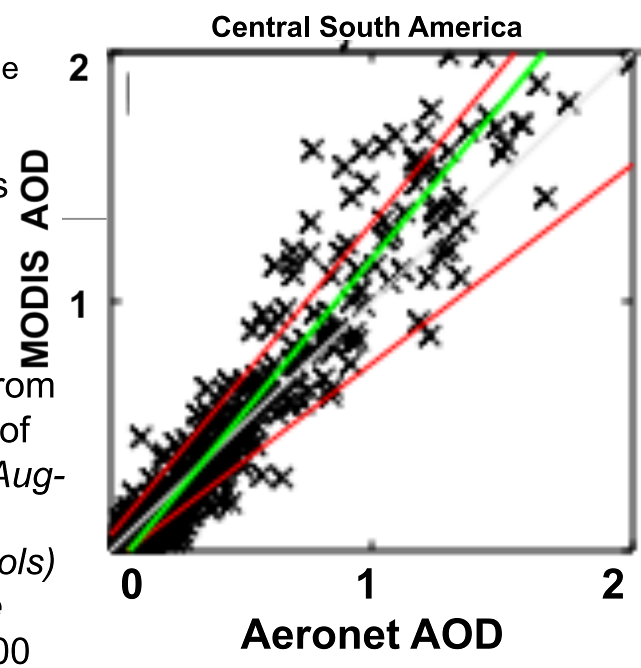
Region & season characteristics: Central region of Brazil is mix of forest, cerrado, and pasture and known to have low AOD most of the year except during biomass burning season

***(Dominating factors leading to Aerosol Estimate bias)*:**

1.Large positive bias in AOD estimate during biomass burning season may be due to wrong assignment of Aerosol absorbing characteristics. (Specific explanation) a constant Single Scattering Albedo ~ 0.91 is assigned for all seasons, while the true value is closer to ~0.92-0.93.

[Notes or *exceptions*: Biomass burning regions in Southern Africa do not show as large positive bias as in this case, it may be due to different optical characteristics or single scattering albedo of smoke particles, Aeronet observations of SSA confirm this]

2. Low AOD is common in non burning season. In Low AOD cases, biases are highly dependent on lower boundary conditions. In general a negative bias is found due to uncertainty in Surface Reflectance Characterization which dominates if signal from atmospheric aerosol is low.



(Example) : *Scatter plot* of MODIS AOD and AOD at 550 nm vs. Aeronet from *ref.* (Hyer et al, 2011) *(Description Caption)* shows severe *over-estimation* of MODIS Col 5 AOD (dark target algorithm) at *large AOD* at 550 nm during *Aug-Oct* 2005-2008 over Brazil. *(Constraints)* Only best quality of MODIS data (*Quality =3*) used. Data with scattering angle *> 170 deg* excluded. *(Symbols)* **Red Lines** define regions of *Expected Error (EE)*, ***Green** is the fitted slope*

***Results:* Tolerance**= 62% within **EE**; RMSE=0.212 ; **r2**=0.81; **Slope**=1.00 **For Low AOD** (<0.2) **Slope**=0.3. **For high AOD** (> 1.4) **Slope**=1.54

***Reference**:* Hyer, E. J., Reid, J. S., and Zhang, J., 2011: An over-land aerosol optical depth data set for data assimilation by filtering, correction, and aggregation of MODIS Collection 5 optical depth retrievals, Atmos. Meas. Tech., 4, 379-408, doi:10.5194/amt-4-379-2011

Presenting Data Quality via Web service

- Once we know what to present, and how to present, and where to get the information from, we can build a service that on a URL request can return an XML, from which a well-organized web page can be rendered.
- This is just one step towards an ideal situation when all the aspects of quality can reside in separate modules that can be searched for based on ontology and rulesets, and then assembled and presented as html page based on user selection criteria.

The MDSA Semantic Advisor

- Provides caveats for intercomparison based on user selections
  - Parameter, Dataset
  - Satellite, Orbit (derived from Dataset)
- Semantic Advisor knits together ontology and rulesets to generate advisories
  - Advisories describe caveats about the differences between two data products
- Semantic Advisor works as a standalone web service
  - Called by Giovanni with input data selections in XML
  - Returns an XML file with the differences between the datasets

Multi-Sensor Data Synergy Advisor (MDSA), AIST-08-0071

Conclusions

- The time is ripe for addressing quality of satellite data
- No consistent framework exists for remote sensing data quality
- Systematizing quality aspects requires:
  - Identifying aspects of quality and their dependence of measurement and environmental conditions
  - Piling through literature
  - Developing Data Quality ontology
  - Developing rulesets to infer pieces of knowledge to extract and assemble
- Presenting the data quality knowledge with good visual, statement and references

Needs identified:

- An end-to-end approach for assessing data quality and providing it to users of the data framework
- Recommendations for future mission on how to address data quality systematically